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Gaussian Acoustic Classifier for the Launch of Three Weapon Systems

by Christine Yang and Geoffrey H. Goldman

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14. ABSTRACT

The U.S. Army is interested in locating and classifying hostile weapons fire to improve the Soldiers' real-time situational awareness. Acoustic localization systems such as the Unattended Transient Acoustic MASINT System (UTAMS) have been demonstrated in theater. However, developing a classifier algorithm is a difficult problem due to atmospheric and propagation effects as well as acoustic interference and noise. Techniques were developed to accurately classify acoustic weapons system fire. Robust features were calculated in the time domain and used to train a Gaussian classifier. The algorithm was tested and trained using data collected in 2005, 2006, and 2011. The performance of the algorithm was similar to the results obtained by other researchers, but with significantly less computational complexity.

15. SUBJECT TERMS

Acoustic classifier, weapon system, Gaussian

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1. Introduction

The U.S. Army is interested in classifying hostile weapons fire to improve the Soldiers' real-time situational awareness and provide the Soldier with actionable information (*1*). Acoustic localization systems such as the Unattended Transient Acoustic MASINT System (UTAMS) have been demonstrated in theater; however, a robust acoustic classification system for weapons system fire has not (*2*). Classification is a much more difficult problem than localization since the actual signature is analyzed, not differential time delays.

Most classifiers are developed using supervised learning algorithms. A standard approach is to use a Bayesian decision theory with Gaussian likelihood functions that minimize the probability of error. This algorithm minimizes the Mahanalobis distance between classes with an estimated offset term. Robust features are needed to discriminate between the launch of direct-fire weapons, such as small arms and rockets, and indirect fire weapons, such as mortars, and to discriminate between large- and small-caliber weapons.

2. Signatures

The classifier was trained and tested with data collected by U.S. Army Research Laboratory in 2005, 2006, and 2011. The data were collected and processed on the launch of weapons systems such as rockets, rifles, and mortars. Tetrahedral microphone arrays were placed in different terrains at different distances from the launching points under various atmospheric conditions. The acoustic data were collected at a 1-kHz sample rate for the 2005 and 2006 measurements and at a 10-kHz sample rate for the 2011 measurements.

Acoustic signatures become corrupted from atmospheric and multipath effects due to terrain, acoustic interference, noise, and signal saturation. As a result, signatures look very different even within the same target class. Several target signatures measured at different field tests are shown in figures 1–3.

When compared to the other target classes, signatures can look alike or vastly different. It is difficult to visually identify features to differentiate between target classes.

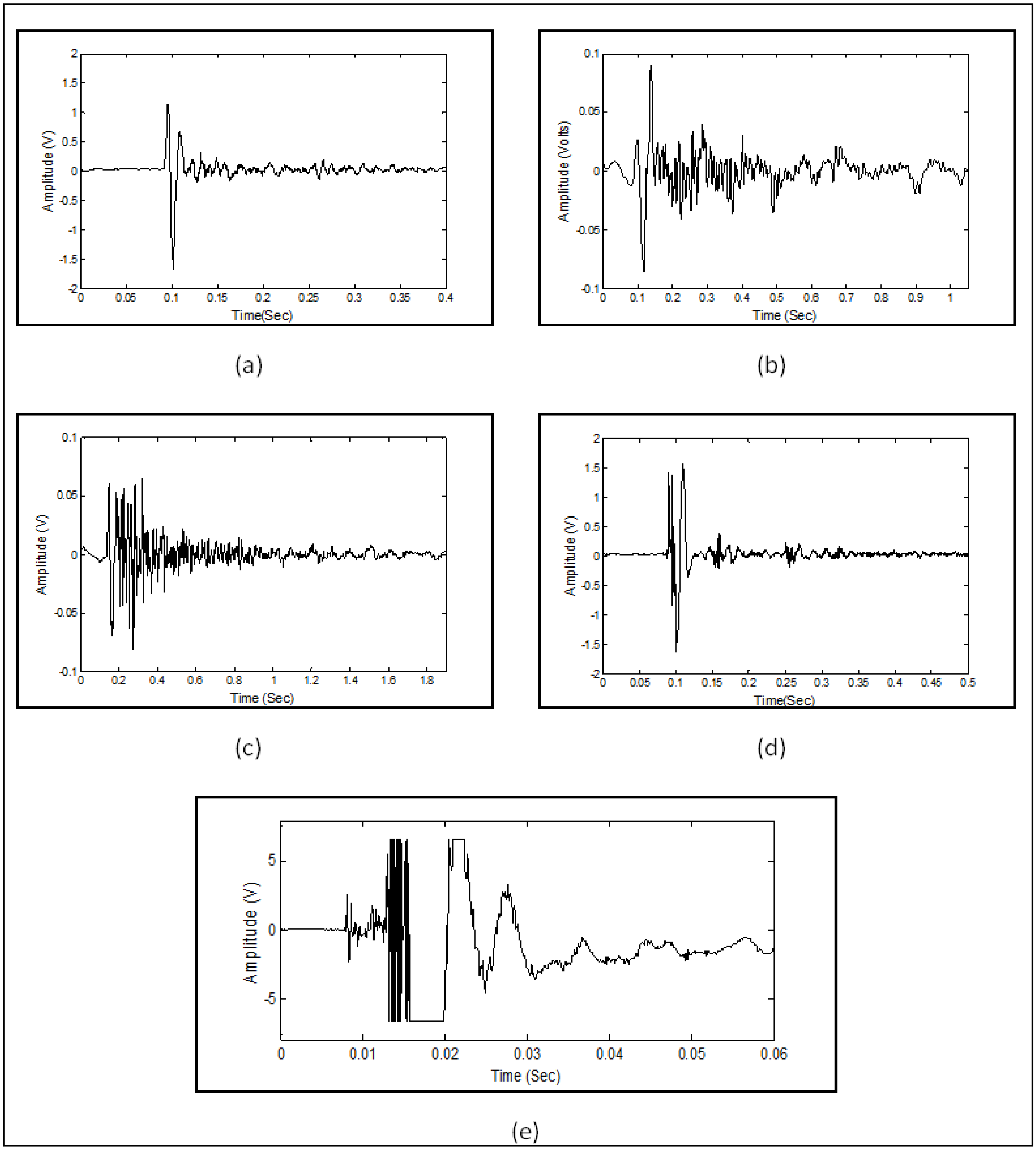


Figure 1. (a) Target 1, 2011, (b) Target 1, 2006, (c) Target, 2006, (d) Target 1, 2011, and (e) Target 1, 2011 (signal saturated).

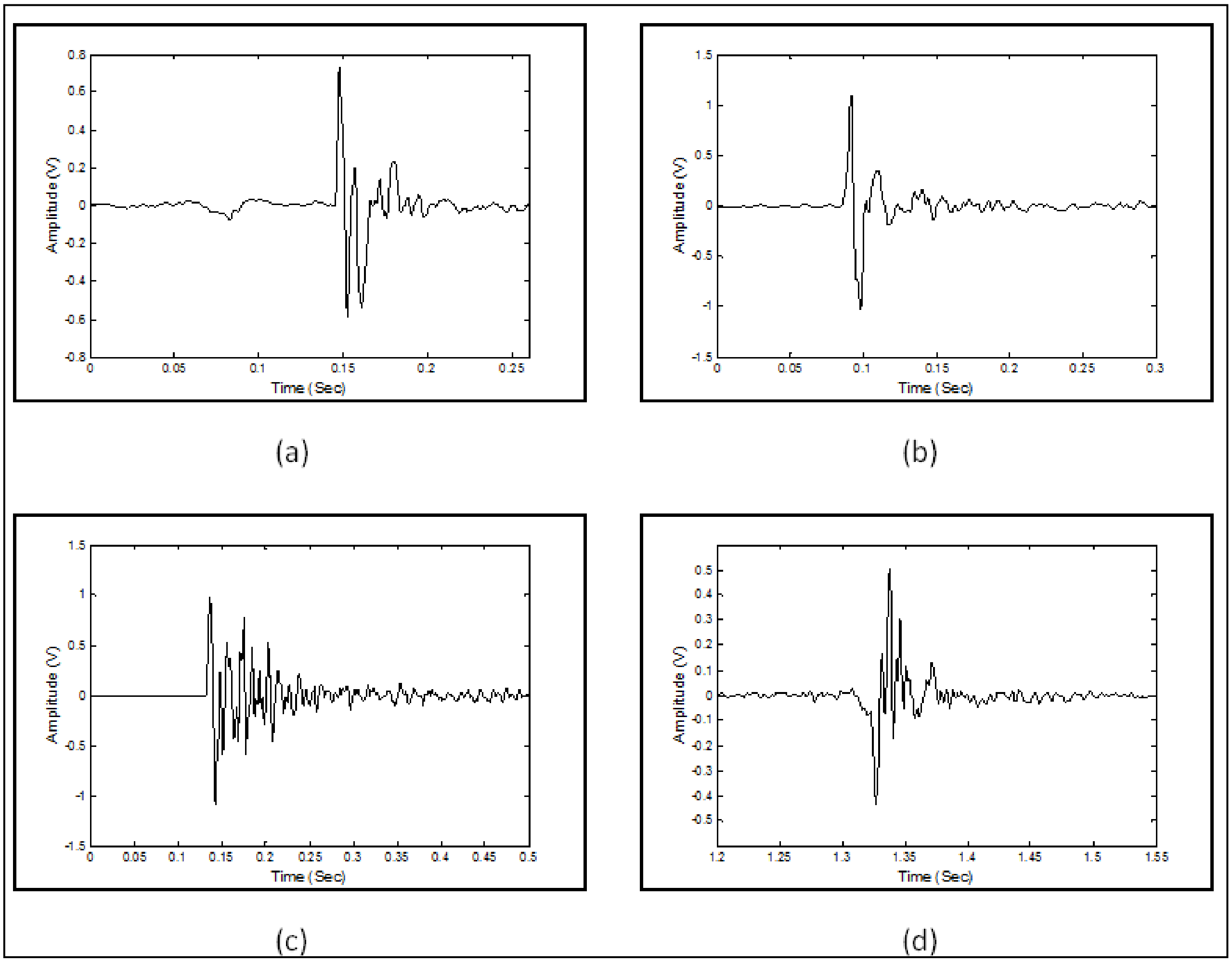


Figure 2. (a) Target 2, 2005, (b) Target 2, 2005, (c) Target 2, 2005, and (d) Target 2, 2005.

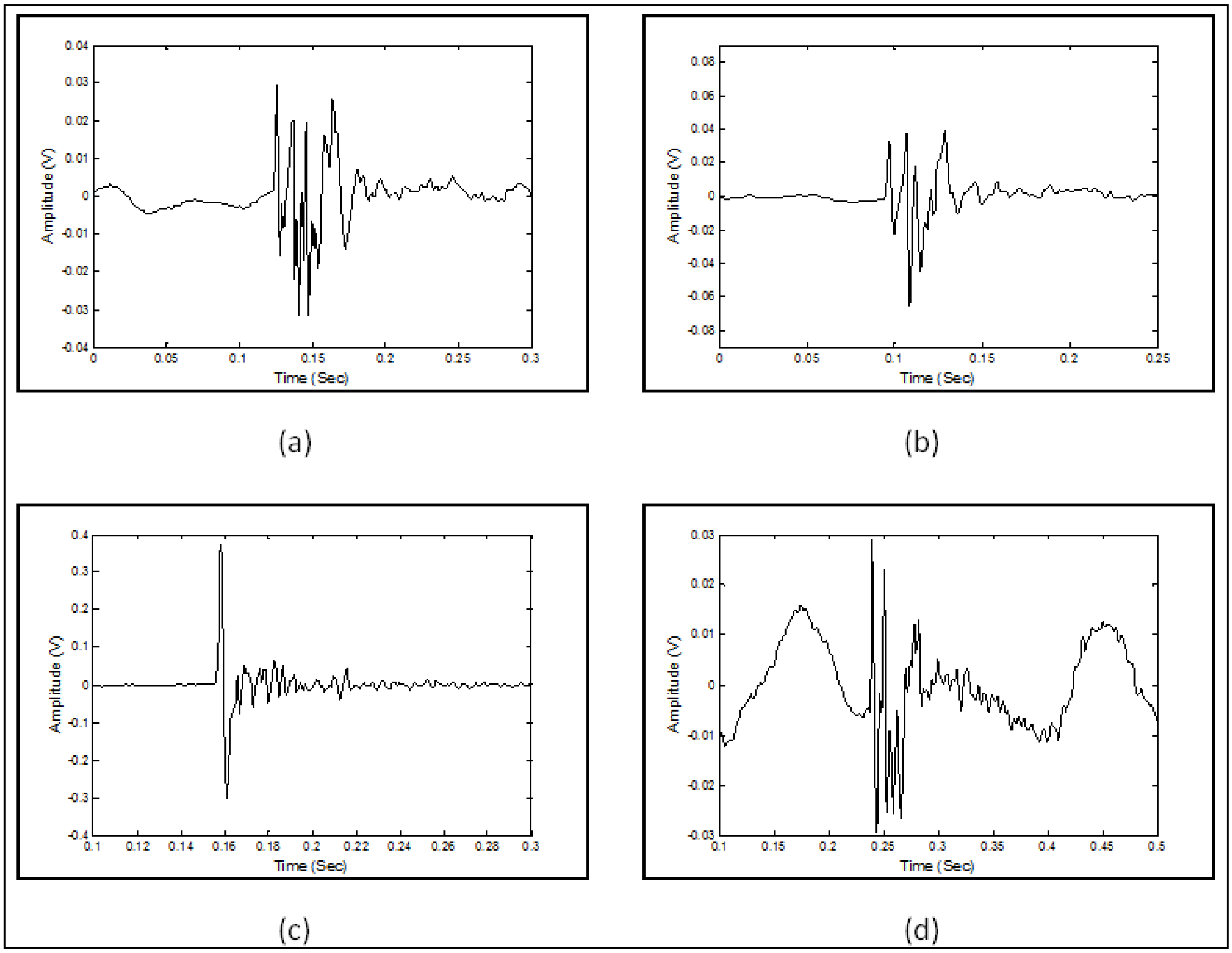


Figure 3. (a) Target 3, 2005, (b) Target 3, 200,5 (c) Target 3, 2005, and (d) Target 3, 2005.

3. Features

The classification algorithm was trained on features estimated from signatures for each target class. Several strategies were considered for selecting the features. Signatures were visually analyzed in the time domain, Fourier domain, and the Cepstral domain. The beginning part of the time domain data, where the direct path hits the sensor before the waves reflected by the terrain and other surrounding objects, was used to generate 10 features. Figure 4 shows the various paramaters in the signature that were estimated and used to calculate features.

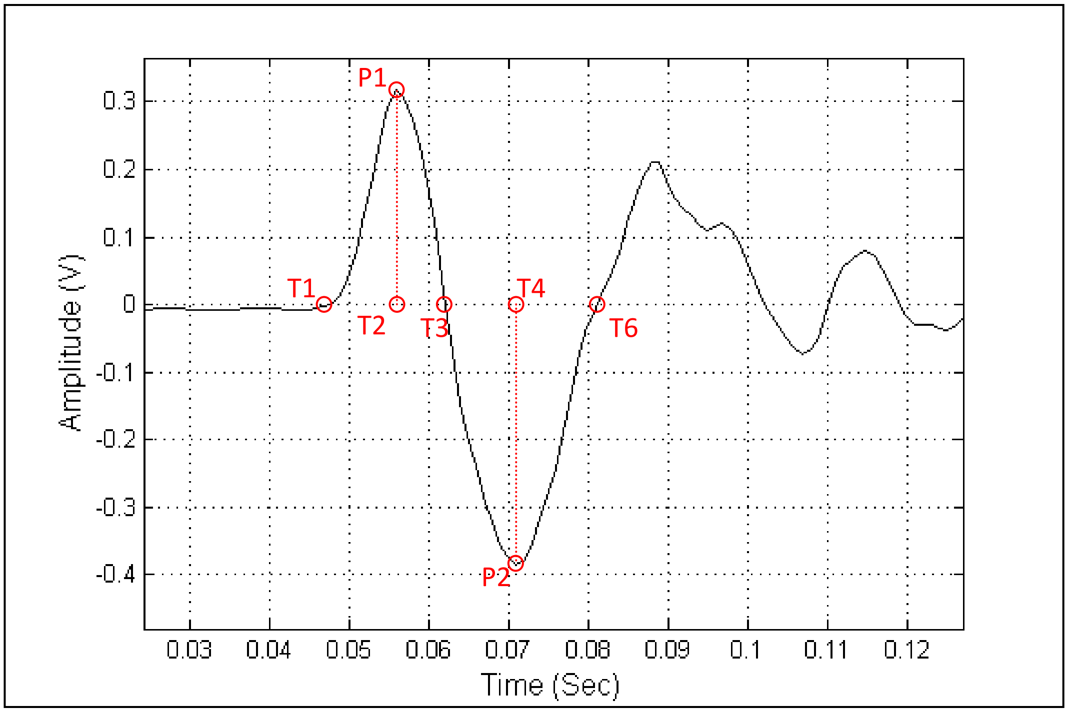
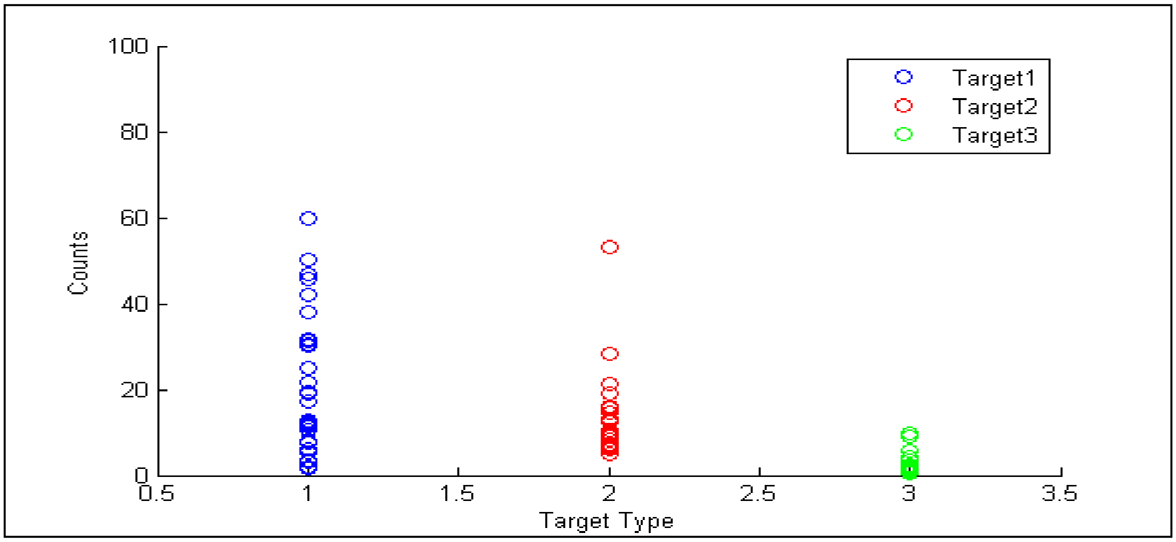


Figure 4. Diagram of the parameters used to estimate the features. 'T' represents the time when the signal crossed zero amplitude or the red vertical line. 'P' represents the value of the positive or negative peak.

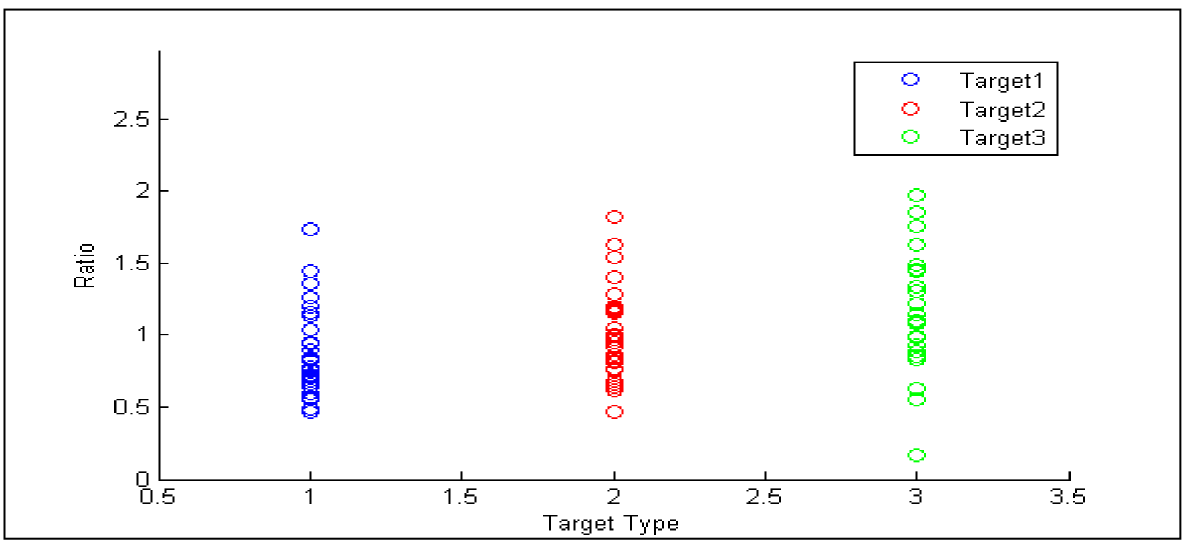
The features selected were based upon amplitude, time duration, and various ratios. The features selected are as follow:

1. Average amplitude (square root of energy)
2. T3-T1
3. T5-T3
4. Max over Min
5. Average of max and min over average amplitude
6. T3-T1 over T5-T3
7. T4-T2 over T5-T1
8. P1 over T3-T1
9. P2 over T5-T3
10. (8)/(9)

One-dimensional plots of the values for each feature and target class are shown in figures 5–9.

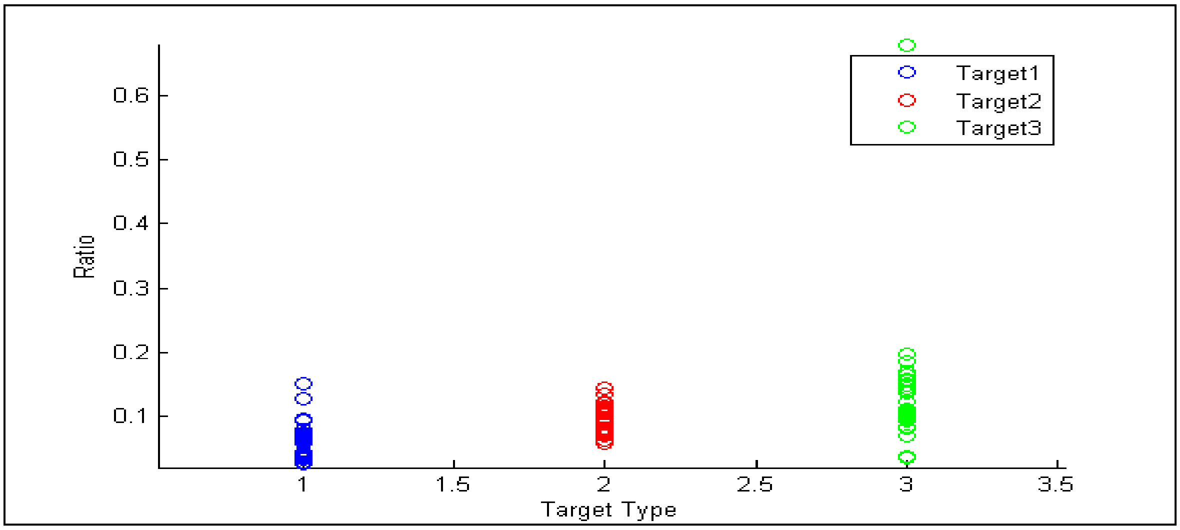


Average Amplitude

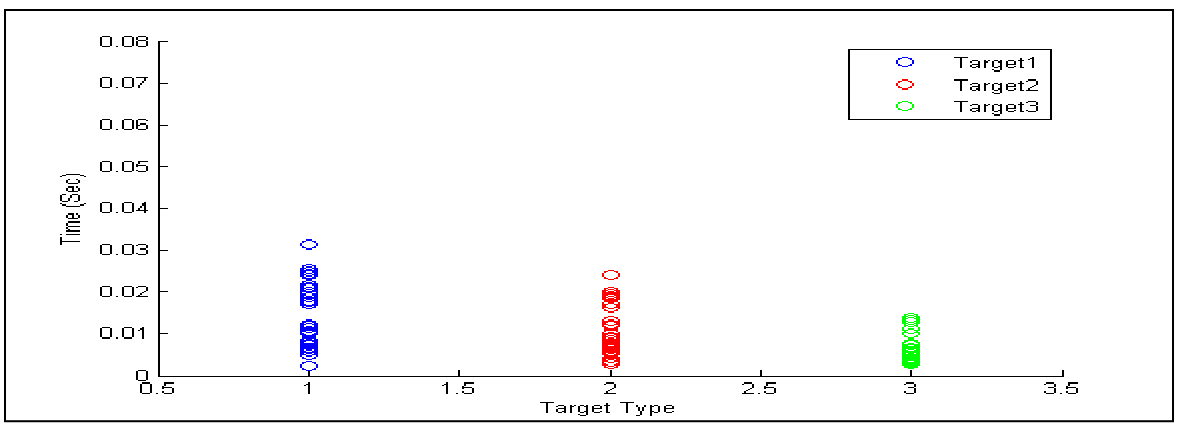


Maximum peak over trough

Figure 5. Feature values (average amplitude and maxium peak over trough) for targets 1, 2, and 3.

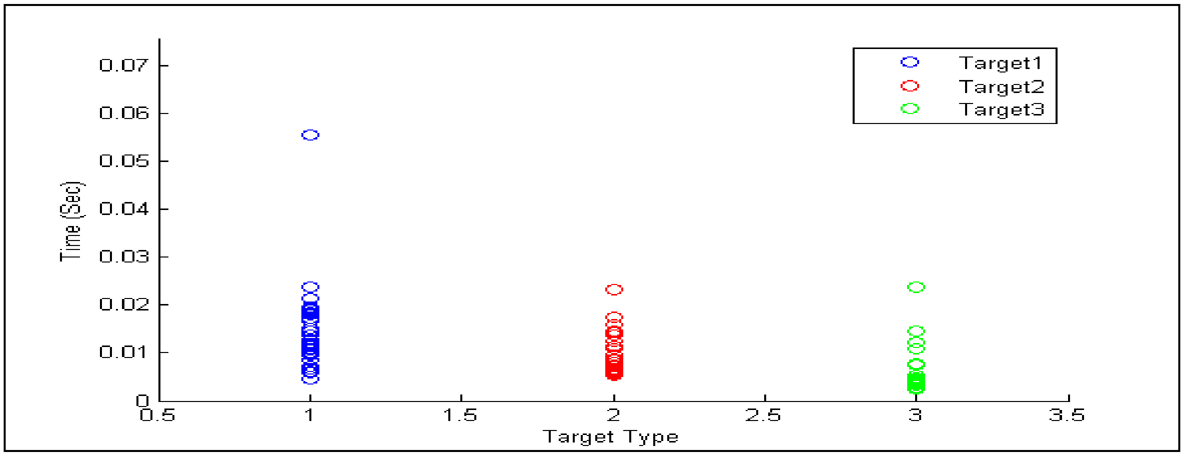


Average of Max and Min over Average Amplitude

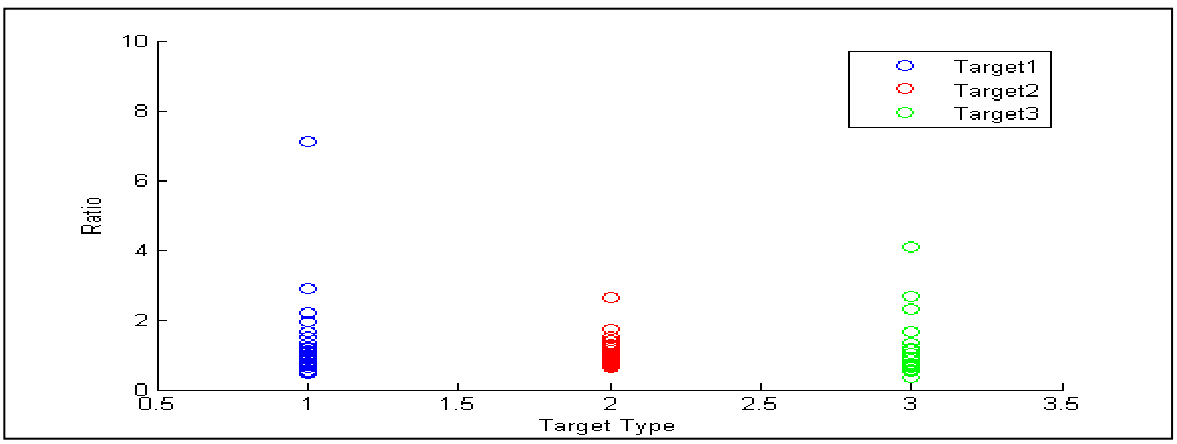


T3-T1

Figure 6. Feature values (average of max and min over average amplitude and T3-T1) for targets 1, 2, and 3.

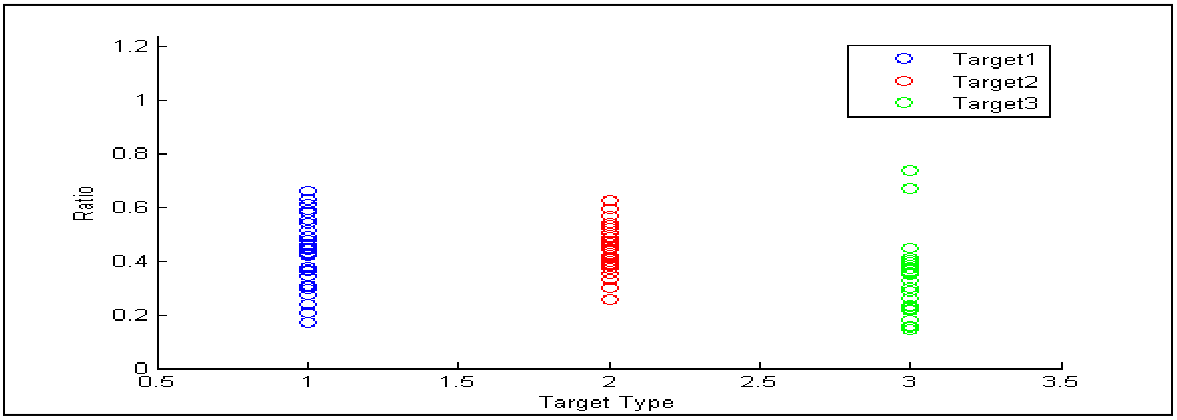


T5-T3

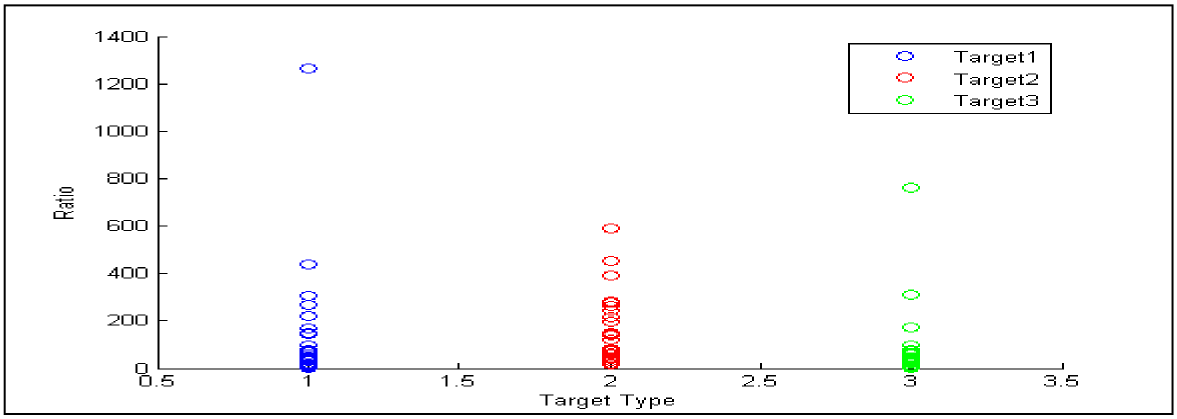


T3-T1 over T5-T3

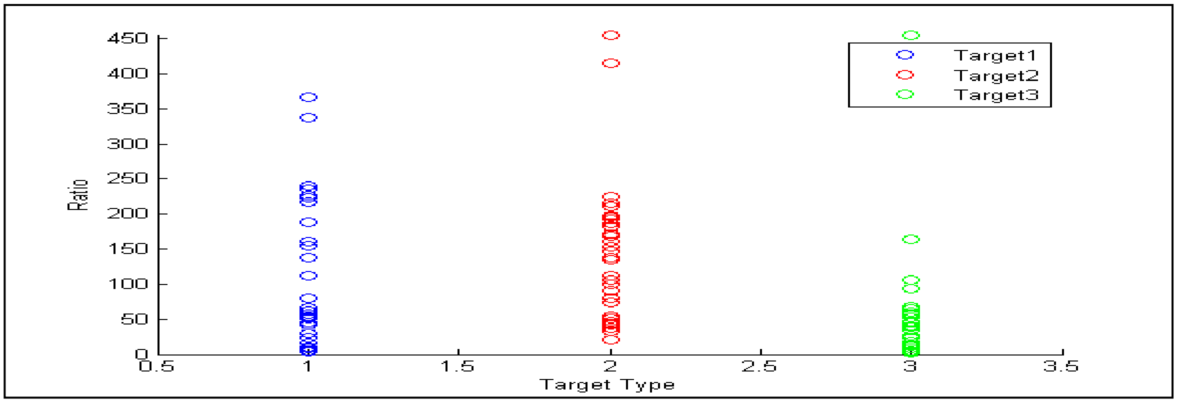
Figure 7. Feature values (T5-T3 and T3-T1 over T5-T3) for targets 1, 2, and 3.



T4-T2



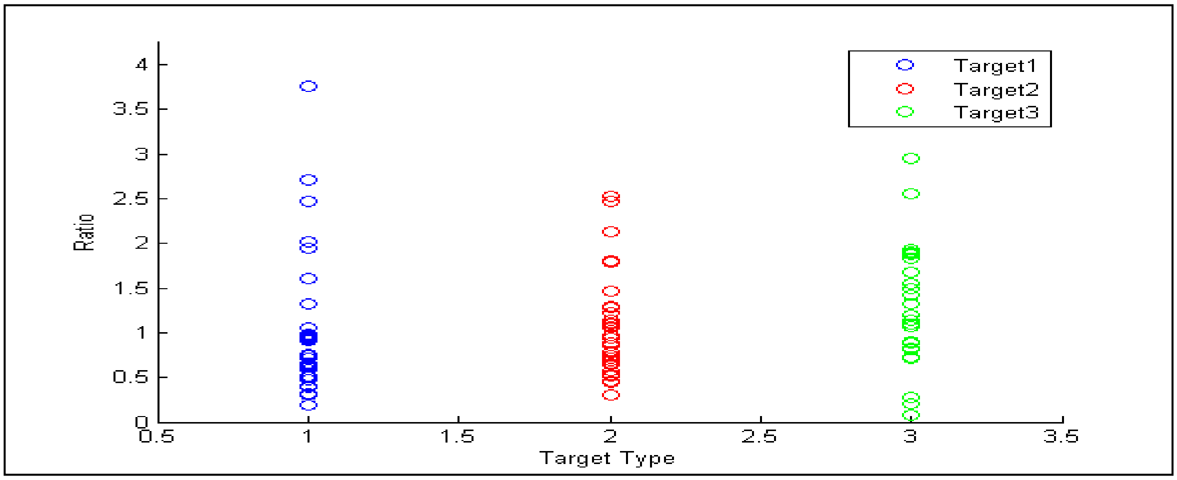
P1 over T3-T1



(i)

P2 over T5-T3

Figure 8. Feature values (T4-T2, P1 over T3-T1, and P2 over T5-T3) for targets 1, 2, and 3.



(P1 over T3-T1)/(P2 over T5-T3)

Figure 9. Feature values ([P1 over T3-T1]/[P2 over T5-T3]) for targets 1, 2, and 3.

4. Classification Algorithm

The classification algorithm is a three-class Bayesian classifier with Gaussian likelihood functions. The probability of error is minimized and the prior probabilities for each class are assumed to be equal. The discrimination function is given by

$$g_i(x_j) = (x_j - \mu_i)^T \Sigma_i^{-1} (x_j - \mu_i) + \log|\Sigma_i|, \tag{1}$$

where x_j is a feature vector for the j^{th} test point, μ_i is the mean vector for the i^{th} class, Σ_i is the estimated covariance matrix for the i^{th} class, and $|(\cdot)|$ denotes determinant (*3*). Test data were classified based upon minimizing the value of the discrimination function in equation 1. The mean and covariance matrix were calculated using all the data except the test data being evaluated.

Several modifications to the feature values were evaluated. First, each feature was normalized by substracting its mean and dividing by the standard deviation. In addition, two methods were used to decrease the effect of outliers on the estimated statistics used in the discrimination function. The first method replaces feature values that are over 2.5 standard deviations of mean with that value. The second method is to square root the features values. This will reduce the size of values much greater than one and increase the size of very small positive values. Listed in tables 1–9 are confusion matrices for the classification algorithm with several modifications to the feature values.

Table 1. Classification results for 95 signatures with no modifications.

	Classified as Target1	Classified as Target2	Classified as Target3	Correct Classification Rate
Actual Target1	23	12	0	66%
Actual Target2	3	28	1	88%
Actual Target3	1	1	26	93%

Table 2. Classification results for 95 signatures with feature normalization.

	Classified as Target1	Classified as Target2	Classified as Target3	Correct Classification Rate
Actual Target1	23	12	0	66%
Actual Target2	3	29	0	91%
Actual Target3	2	1	25	89%

Table 3. Classification results for 95 signatures with the square root function applied to the feature values.

	Classified as Target1	Classified as Target2	Classified as Target3	Correct Classification Rate
Actual Target1	23	11	1	66%
Actual Target2	5	27	0	84%
Actual Target3	1	1	26	93%

Table 4. Classification results for 95 signatures with the square root function applied to the feature values, then normalization.

	Classified as Target1	Classified as Target2	Classified as Target3	Correct Classification Rate
Actual Target1	23	11	1	66%
Actual Target2	6	26	0	81%
Actual Target3	1	1	26	93%

Table 5. Classification results for 95 signatures with outlier mitigation applied to the feature values.

	Classified as Target1	Classified as Target2	Classified as Target3	Correct Classification Rate
Actual Target1	26	9	0	74%
Actual Target2	8	24	0	75%
Actual Target3	1	1	26	93%

Table 6. Classification results for 95 signatures with outlier mitigation and normalization.

	Classified as Target1	Classified as Target2	Classified as Target3	Correct Classification Rate
Actual Target1	26	9	0	74%
Actual Target2	9	23	0	72%
Actual Target3	2	1	25	89%

Table 7. Classification results for 95 signatures with the square root function applied to the feature values and outlier mitigation.

	Classified as Target1	Classified as Target2	Classified as Target3	Correct Classification Rate
Actual Target1	23	11	1	66%
Actual Target2	12	20	0	63%
Actual Target3	2	1	25	89%

Table 8. Classification results for 95 signatures with the square root function applied to the feature values, outlier mitigation, then normalization.

	Classified as Target1	Classified as Target2	Classified as Target3	Correct Classification Rate
Actual Target1	23	11	1	66%
Actual Target2	12	20	0	63%
Actual Target3	2	1	25	89%

Table 9. Average correct classification rate among all methods.

Feature Modification	Average Correct Classification Rate
None	82.3
Normalization	82
With SQRT	81
SQRT and Normalization	80
Outlier Mitigation	80.6
Outlier Mitigation and Normalization	78.3
SQRT and Outlier Mitigation	72.6
SQRT, Outlier Mitigation and Normalization	72.6

Surprisingly, the classification algorithn shown in equation 1 with no feature modifications had the best results. However, we recommend using the outlier mitigation method because the correct classificaiton rate is spread out more evenly among target classes. The results obtained are similar to results from other researchers (*4*).

5. Conclusion

A classification algorithm was implemented using Bayesian decision theory with Gaussian likelihood functions and 10 features calculated using parameters estimated in the time domain. The algorithm was tested using 95 signatures. Several techniques that modify the values of the features were evaluated. The modifications had a small or negative impact on the classification results. The average correct classification rate was 82% using features with no modification. The results indicate that the approach is reasonable. However, there are too many features compared to the number of training data to reliably predict the performance of the algorithm. Future efforts will need to reduce the number of features and/or increase the amount of test data.

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